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The Effect of Heuristics on Stock Buying Decisions of Individual Investors: Evidence from the Nigerian stock exchange

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Abstract

Empirical evidence from developed countries have established that heuristics biases do have significant effect on individuals' investment decisions in stock market, but there is very limited number of studies conducted in less developed countries especially in Sub- Saharan Africa and Nigeria in particular. In view of this, this paper attempts to bridge the gap by examining the effect of heuristics on individuals' investors stock buying decisions based on the Nigerian stock market context using a survey strategy. A sample of 400 questionnaires were administered to individual investors, the data collected were analysed with multiple-linear regression using SPSS Software. The findings revealed that heuristics biases have significant effect on individual investors stock buying decisions with $R^2 = .563$, $F(5, 211) = 79.31$, $p < .001$. The study further revealed that gambler's fallacy, availability bias and overconfidence had the highest effect, indicating that investors exhibiting these heuristics may tend to used locally available information, based their selling decisions on purchase price, and may overestimate their ability to process information while making stock buying decisions. The study, proposed that investors need to be aware of these biases and its implication on their subsequent investment performance. The security market operators need to create more awareness about these biases, so as to enable individual investors make an informed decision about the stock they buy.

Keywords: Heuristics biases, Individual investors, Stock buying decision, Nigerian stock market.

1.1 Introduction

Conventional financial theory accept that speculators are normal riches maximisers, following essential budgetary principles and constructing their venture techniques absolutely in light of the hazard return thought as the components anticipated that would impact venture choices (Baker, Hargrove, and Haslem 1977). Traditional economics theory expects that individuals are sound specialists who settle on choices equitably to exploit the opportunities accessible to them. Investors generally consider themselves objective and intelligent, yet with regards to investing, their passionate tendencies imbued thought designs and mental predispositions, decides how they see the world and how they settle on choices in the capital market. The presence of such inclinations among individual speculators influences the manner in which they see the risk and return relationship when settling on venture choices. Global financial markets have presented new difficulties for speculators while settling on venture choices in securities exchange. This is because the activities of all investors are based on continuous decision-making in an uncertain environment that offers a probable outcome. Heuristics are general decision making procedures that depend on little data, yet regularly right (Obara, 2015). As per Shah and Oppenheimer (2008), a heuristic is a dependable guideline or strategy that causes one take care of complex issues quicker than when they would when figuring. Heuristics offer the client the capacity to investigate a few signs and elective decisions in basic leadership. Likewise, heuristics lessen crafted by recovering and putting away data in memory, streamlining the basic leadership process by diminishing the measure of coordinated data fundamental in settling on the decision or condemning (Shah and Oppenheimer, 2008). This study will look at representativeness, overconfidence, gamblers fallacy and anchoring heuristics and their influence on stock buying decisions of individual investors at the Nigerian stock market.

2.0 Review of Empirical Literature

The outcome of the global financial crisis and the resultant unexplained unpredictability and market anomalies have raise doubt about the establishment of the Efficient Market Hypothesis and require the interest for another worldview of modern financial theory. In the ongoing decades, financial experts have endeavoured to come back to the first point to see how human psychology influences investors' financial decisions. This evolution leads to the emergence of a new paradigm of financial research known as the behavioural finance. Being a generally new field in finance, behavioural finance applies psychology to study why people buy or sell financial assets based on the psychological principles of decisions making. Rather than totally supplanting traditional finance, behavioural finance assumes a corresponding job in understanding the issues that the traditional finance seems to neglect to comprehend (Subrahmanyam, 2007). Behavioral finance spotlights on how investors translate and act on data during their investment decision making. The standard supposition fundamental to traditional financial theory, that investors do dependably act in an impartial way is loose in behavioural finance. Behavioral finance researchers have reported a lot of proof that speculators' feelings and psychological blunders are related with different financial market oddities. Xu (2010) opined that behavioural finance recommended that some market marvels can be better comprehended by considering that investors are not completely rational and that human unsteadiness impacts the financial decisions of investors. Applying some mental hypotheses, behavioural finance shows that investors can't refresh their convictions or settle on judgments and choices under dangerous circumstances as effectively as proposed by the traditional finance theories. Rather they could be one-sided in gathering, accepting, and refreshing data, and in making inferences. For instance, investors may frame their convictions by utilizing general guidelines or some improved strategies (Slovic, 1972; Tversky and Kahneman, 1974).

2.1 Heuristic hypothesis

Ritter (2003) characterizes heuristics as the dependable guidelines, which makes decision making simpler, particularly in unpredictable and unverifiable condition. It decreases the unpredictability of surveying probabilities and foreseeing values to more straightforward judgments (Kahneman and Tversky, 1974). Kahneman and Tversky were the main scholars to examine the elements having a place with heuristics when they presented representativeness, availability bias, and anchoring (Kahneman and Tversky, 1974). Waweru et al. (2008), likewise list two components named Gambler's fallacy and Overconfidence into the heuristic hypothesis.

2.1.1 Representativeness: This alludes to the level of closeness that an occasion has with its parent populace (DeBondt and Thaler, 1985) or how much an occasion looks like its populace (Kahneman and Tversky, 1974). The representativeness heuristic attests that when individuals assess the likelihood of uncertain events, they have a tendency to anticipate by looking for the nearest coordinate in its basic properties to past patterns (Tversky and Kahneman, 1974; Kahneman, Slovic and Tversky, 1982). Representativeness may result in a few inclinations, for example, individuals put excessive weight on late involvement and overlook the normal long-haul rate (Ritter, 2003). An ordinary case for this predisposition is that investors regularly induce an organization's high long haul development rate after a few fourth of expanding (Waweru et al., 2008). In securities exchange, representativeness prevails, when investors try to purchase "hot" stocks rather than poorly performed ones. Empirical studies within the behavioral finance approach have discovered that this heuristic influences the investor's choice while assessing stocks (Barberis, Shleifer and Vishny, 1998; Bloomfield and Hales, 2002; Frieder 2004, 2008; Kaestner, 2006; Alwathainani, 2012; Ramzi, 2013).

2.1.2 Gamblers' fallacy: The gambler's fallacy is the false belief in a negative correlation between independent trials of a random process (Tversky and Kahneman, 1971). This arises when people predict inaccurately the reverse points which are considered as the end of good (or poor) market returns (Waweru et al., 2008). It can be regarded as the false belief that a random event is less likely to occur if the event has occurred recently (Suetens and Tyrans, 2011). Chen, Tobias, and Shue (2016), have found consistent evidence of negative autocorrelation in decision making that is unrelated to the merits of the decision makers considered. They found those decision makers usually underestimate the likelihood of sequential streaks occurring by chance—leading to negatively autocorrelated decisions that result in errors. The negative autocorrelation is observed to be stronger among more moderate and less experienced decision makers, following longer streaks of decisions in one direction. Huber, Kirchler, and Stockl (2010) also find behaviour consistent with the gambler's fallacy in a lab experiment, as the frequency of betting on heads decreases after streaks of heads and vice versa for tails.

2.1.3 Anchoring: This is a phenomenon that occurs in the situation when people use some initial values to make the estimation, which is biased toward the initial ones as different starting points yield different estimates (Kahneman & Tversky, 1974). In the financial market, anchoring arises when a value scale is fixed by recent observations. Investors always refer to the initial purchase price when selling or analysing their stock. Thus, today prices are often determined by those of the past. Anchoring makes investors to define a range for a share price or company's income based on the historical trends, resulting in under-reaction to unexpected changes. Anchoring has some connection with representativeness as it also reflects that people often focus on recent experience and tend to be more optimistic when the market rises and more pessimistic when the market falls (Waweru et al., 2008).

2.1.4 Overconfidence: This prevails when people overestimate the reliability of their knowledge and skills (DeBondt & Thaler, 1985, Hvide, 2002). Investor overconfidence describes that people who are overconfident about the precision of private information tend to overestimate their ability to evaluate securities in financial markets (Barber and Ordean, 2001, Ritter, 2003). Many studies show that excessive trading is one effect of investor's overconfidence. Investor overconfidence results in an incorrect valuation of stocks in response to information announcements, an outcome made worse by biased self-contribution if the initial prediction is confirmed by real market movement in the next period (Ackert & Deaves, 2009; Hirshleifer, 2001). This pair of psychological biases may work continuously in financial markets, pushing stock prices to increase (decrease) further and further, which increases the excess volatility of stock returns and generates stock prices bubbles and crashes (Debondt and Thaler, 1985).

2.1.5 Availability bias: This happens when people make use of easily available information excessively. In the stock trading area, this bias manifests itself through the preference of investing in local companies which investors are familiar with or easily obtain information, despite the fundamental principles so-called diversification of portfolio management for optimization (Waweru et al., 2008).

In this research, five components of heuristics: overconfidence, gambler's fallacy, availability bias, anchoring, and representativeness are included in the model.

2.2 Stock buying decision

Odean (1999) provides several understandings about the preferred stocks that individual investors would like to buy. Selling decisions mainly prioritize winning stocks; whereas, buying decisions are related to both prior winning and losing stocks. Odean states that the buying decisions may be a result of an attention effect. When deciding of the stock purchase, people may not find a good stock to buy after considering systematically the thousands of listed securities. They normally buy a stock having caught their interest and maybe the greatest source for attention is from the tremendous past performance, even good or bad. Barber and Odean (2002) already prove that the selling decisions are less determined by attention than buying decisions in the case of individual investors. To give this conclusion, they create the menu of attention-grasping stocks with several criteria: unusually high trading volume stocks, abnormally high or low return stocks, and stocks including news announcements. Eventually, they explore that the individual investors in their sample are more interested in purchasing these high-attention stocks than selling them. As such, from the viewpoints of behavioural finance, the investor behaviours have a high impact on buying decisions of investors.

2.7 Research gap:

It can be observed from the literature that the findings of different studies vary. The differences in findings from the various studies might be due to different countries and different demographic profiles of the study populations, different methodologies applied, a different set of variables used for the study, different sources and type of data used in the study, and different time periods considered for the study etc. Pompian (2006) assert that education level can affect the prevalence of heuristics biases among individuals. Therefore, the heuristics biases may work differently due to differences in education levels between developed and developing countries. Hence, the heuristics biases and their effects on stock buying decisions among individual investors at the Nigerian stock market needs to be investigated to enable the researcher proper appropriate recommendations and advised the capital market operators in a developing country and Nigeria in particular.

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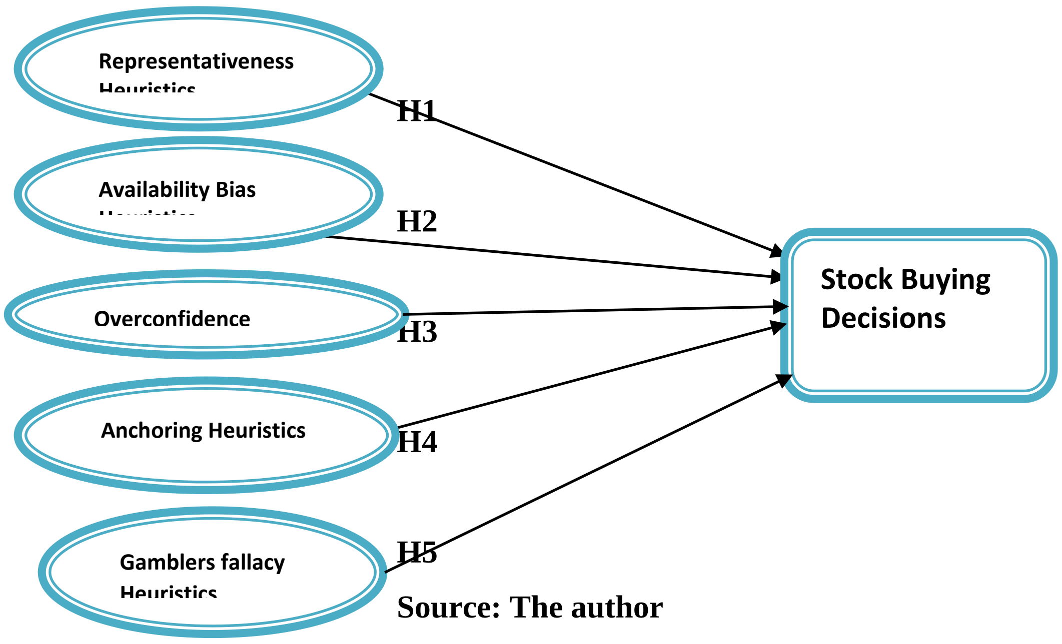
3.0 Methodology

A survey design was adopted for this research work using a structured questionnaire. Hair, Black, Babin, Andersion and Tatham (1998) suggest that with quantitative research, at least 100 respondents should be studied in order to have fit the statistical methods of data analysis. As the research aims at exploring the influence of heuristics biases on stock buying decision of individual investors at the Nigerian stock exchange, a relatively large sample size is recommended. The Taro Yamane (1967) table for sample size determination as reviewed by Glenn (1992) was utilised, using a precision level of +7%, 95% confidence level and P=50% (population attributes) to determine a sample size of 204. An adequate number (400) of questionnaires were sent to individual investors in the hope of receiving more than 200 responses (i.e. an expected response rate of 50%). The number of questionnaires apportioned to each security company was decided based on its brokerage market share in Nigerian stock market. The questionnaires were sent to brokers of the companies who took responsibility for sending to investors randomly. Due to time constraint, only individual investors from ten leading securities companies were chosen. Although investors from these ten companies are not the whole population, but they do account for about 66.41% of the whole population as at 31/12/2017 which can be considered as representative enough to some extent. The data collected were analysed using Pearson correlation and multiple regressions with the SPSS software.

3.1 The research model

Figure 2.2: The research model for studying the influence of heuristics on stock buying decisions of individual investors at the Nigerian stock market.



Source: The author

4.0 Results

4.1 Descriptive Statistics

Respondents' evaluation of their investment decisions were measured using 5 point likert scale ranging from strongly disagree (scale 1) to strongly agree (scale 5). Table .1 reports the descriptive statistics of the items under the heuristics theory and investment decision making. The results shows the mean ratings and standard deviations ranging between 3.32 3 (.902) to 3.406 (.939) respectively. This indicates that all the variables were highly rated by the respondents as all the mean values are above the neutral point (3.0), while the standard deviations are all below 3.0 indicating the absence of significant outliers in the data.

Table 1: Descriptive Statistics of the variables

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	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
RepresentativenessMS	3.3641	.96762	-.089	.165	-.932	.329
AnchoringMS	3.3249	.92633	-.398	.165	-.734	.329
AvailabilityBiasMS	3.3226	.90246	-.269	.165	-.758	.329
InvestDecMaking	3.3970	.93321	-.213	.165	-.692	.329
Gmblers Falacy	3.4055	.93866	-.384	.165	-.622	.329
Overconfidence	3.3548	.91205	-.320	.165	-.747	.329

4.2 Assumption Testing

Multiple regressions have some underline assumptions that need to be tested to avoid data problem and its likely consequences on the final conclusion about the research outcome. These assumptions include the test of normality, homoscedasticity and multicollenearity.

4.2.1 Test of Normality

Data normality for individual measured items was checked by determining the skewness and kurtosis statistics, which are shown in tables 4.1. The skewness and kurtosis statistics of all variables were found to be less than ±1, which indicated no deviation from data normality. Also normality can be tested by inspecting the normal P-P and Q-Q plots. The actual shape of the distribution of the data can be seen in the Histograms provided (in figure 1a). For this data of our study, the scores appear to be reasonably normally distributed. This is also supported by an inspection of the normal probability plots (labelled Normal Q-Q Plots in figure 1b). In these plots the observed value for each score is plotted against the expected value from the normal distribution. A reasonably straight line suggests a normal distribution, as can be seen below.

Figure 1: The Histogram and Normal P-P Plot

Figure 1a:

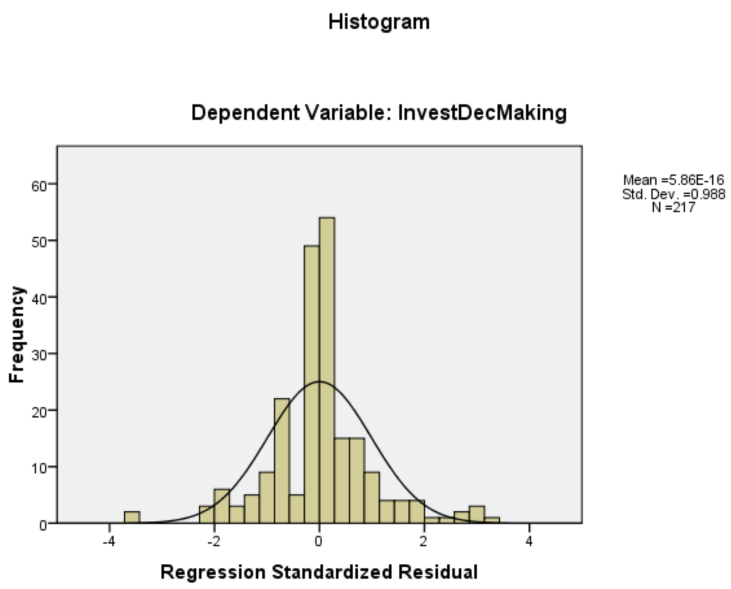
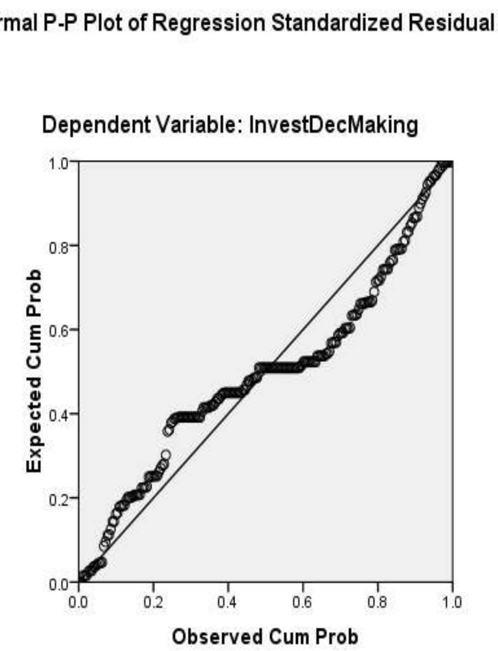


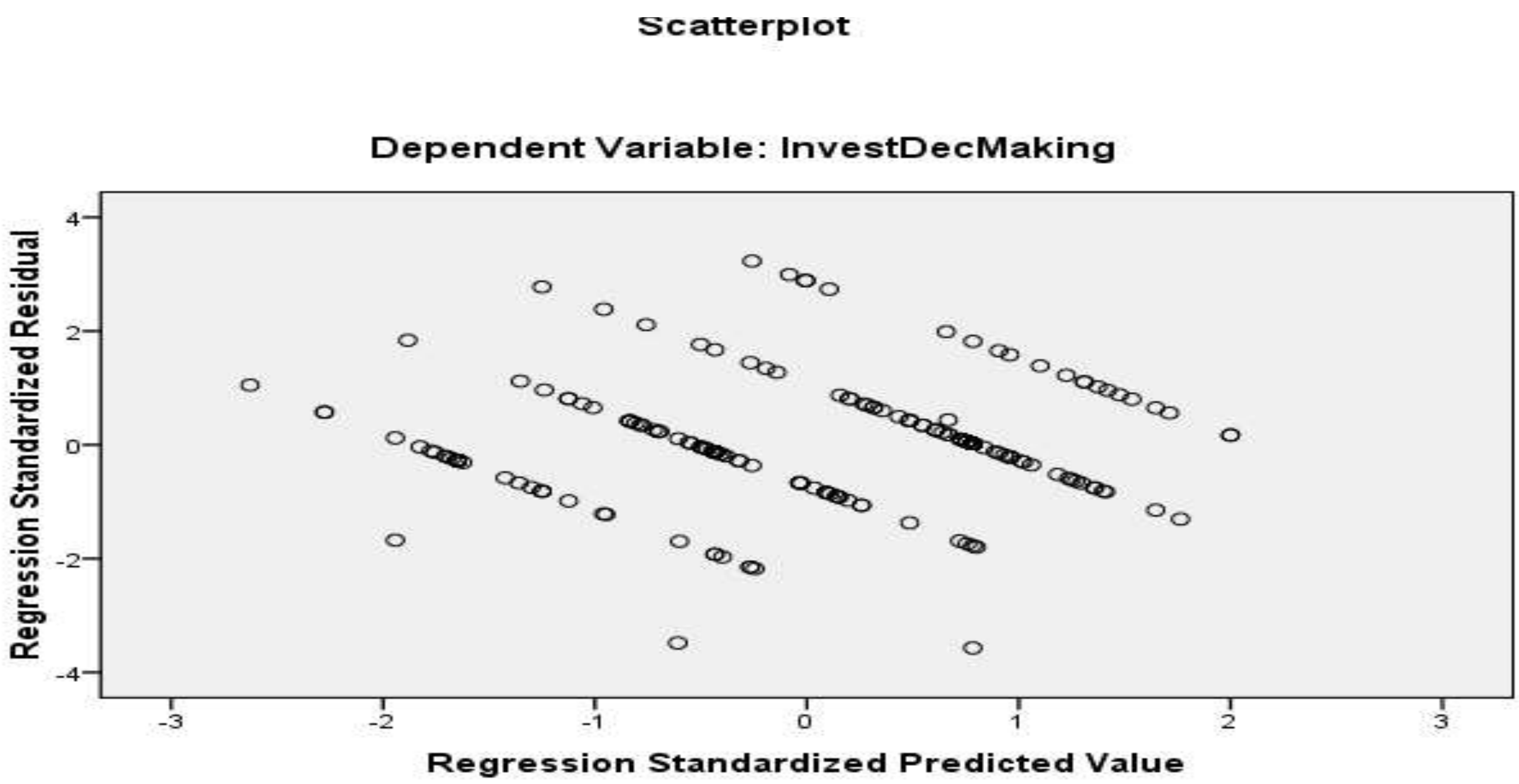
Figure 1b:



4.2.2 Test of Homoscedasticity

Homoscedasticity implies that the fluctuation of errors is the equivalent over all levels of the independent variables (IV). At the point when the fluctuation of errors varies at various values of the IV, heteroscedasticity is demonstrated. As indicated by Berry and Feldman (1985) and Tabachnick and Fidell (1996), slight heteroscedasticity has little impact on significance tests; be that as it may, when heteroscedasticity exist, it can prompt genuine mutilation of discoveries and truly debilitate the examination accordingly expanding the likelihood of a Type I Error. This supposition can be checked by visual examination of a plot of the standardized residuals (the mistakes) by the regression standardized predicted values. Most modern statistical softwares incorporate this as an alternative. Figure 3 demonstrate precedents of plots that may result from homoscedastic and heteroscedastic data. In a normally distributed data, residuals are arbitrarily scattered around 0 (the flat line) giving a generally even dissemination. Heteroscedasticity is shown when the residuals are not equally scattered around the line. Homoscedasticity presumption can be checked by examining the residuals scatterplot and the Normal Probability Plot of the regression stsandardized residuals. In the Normal Probability Plot, the data points supposed to lie in a sensibly straight askew line from base left to upper right. In the Scatterplot of the standardized residuals (as in figure 2), the residuals lie generally rectangularly circulated, with a large portion of the scores amassed in the inside (alongside the 0 focuses). However, there is little proof of systemic pattern in the residuals, this shows little deviations from homoscedasticity supposition.

Figure 2: Scatter Plot for Test of Homoscedasticity



4.2.3 Checking for Outliers

The univariate exceptions were recognized by deciding recurrence dispersions of Z scores of the observed data, as proposed (Kline. 2005). While multivariate anomalies were checked by deciding the Cook Distance and Mahalanobis Distance (D2), which is a proportion of distance in standard deviation units between each observation compared with the mean of all observations (Byrne 2001; Kline, 2005; Hair et al., 2006). A cook distance of more prominent than 1.0 demonstrates a potential anomaly, and a large D2 also distinguishes the case as an extreme measure on at least one factor. A very conservative statistical significance test, for example, $p < 0.001$ is prescribed to be utilized with D2 measure (Kline 2005; Hair et al., 2006). In this study, Mahalanobis distance was estimated utilizing SPSS version 16.00 after it was contrasted with the critical X2 value of 20.52 with corresponding degrees of freedom (df = 5), which was equivalent to the number of independent variables at the probability of $p < 0.001$ (Tabachnick and Fidel 2001). The consequences of multivariate anomalies appear in Table 4.2 which demonstrates that there were no cases with D2 greater than the crtical X2 value of 20.52 as said above. In this manner, no cases were rejected from the data because of outliers.

Table 2: Residual Statistics- Cook Distance and D^2

Statistics	Minimum	Maximum	Mean	Std. Deviation	N
Mahal. Distance	.210	31.525	4.977	4.920	217
Cook's Distance	.000	.135	.006	.016	217
Centered Leverage Value	.001	.146	.023	.023	217

4.2.4 Multicollenearity Test

Collenearity is essentially the assumption that the predictors are not too highly correlated with one another. Collenearity diagnostic was performed to in order to detect the presence of multicollenearity among the variables. This can be achieved by using the correlation matrix (as in table 3) to ascertain that the predictors are not highly correlated. A Pearson bivariate correlation coefficient >.8 between any of the predictors is considered problematic (Tabachnick and Fidel, 2005).

Table 3: Correlation Matrix

IVs	InvestDecMaking	Representativeness	Anchoring	AvailabilityBias	Gmblers Falacy	Overconfidence
Invest DecMaking	**1**					
Representativeness	.645	**1**				
Anchoring	.718	.817	**1**			
AvailabilityBias	.711	.818	.825	**1**		
Gmblers Falacy	.730	.624	.721	.656	**1**	
Overconfidence	.715	.692	.710	.698	.756	**1**

Other measures for checking multicollenearity include the Tolerance value, Variance Inflation Factor, and Condition index. Tolerance is an indicator of how much of the variability of the specified independent is not explained by the other independent variables in the model and is calculated using the formula 1–R2 for each variable. If this value is very small (less than .10), it indicates that the multiple correlation with other variables is high, suggesting the possibility of multicollinearity. The other value given is the VIF (Variance inflation factor), which is just the inverse of the Tolerance value (1 divided by Tolerance). VIF values above 10 would be a concern here, indicating multicollinearity. I have quoted commonly used cut-off points for determining the presence of multicollinearity (tolerance value of less than .10, or a VIF value of above 10). These values, however, still allow for quite high correlations between independent variables (above .9), so you should take them only as a warning sign, and check the correlation matrix. In this example the tolerance value for each independent variable is .729, which is not less than .10; therefore, I have not violated the multicollinearity assumption. This is also supported by the VIF value, which is 1.372, which is well below the cut-off of 10. These results are not surprising, given that the Pearson's correlation coefficient between these two independent variables was only .52 (see Correlations table). If any exceed these values in the results, then one should seriously consider removing one of the highly intercorrelated independent variables from the model.

Table 4: Regression Coefficients

Model		Unstandardized Coef		Standardized Coef	t	Sig.	95% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	.318	.160		1.986	.048	.002	.634					
	RepresentativenessMS	-.040	.077	-.041	-.514	.608	-.191	.112	.645	-.035	-.021	.258	3.869
	AnchoringMS	.171	.087	.170	1.967	.051	.000	.342	.718	.134	.080	.221	4.522
	AvailabilityBiasMS	.264	.084	.256	3.134	.002	.098	.431	.711	.211	.127	.247	4.044
	Gmblers Falacy	.302	.067	.303	4.473	.000	.169	.434	.730	.294	.181	.358	2.794
	Overconfidence	.220	.071	.215	3.083	.002	.079	.361	.715	.208	.125	.338	2.957

a. Dependent Variable: InvestDecMaking

4.2 Findings

Correlation and multiple regression analyses were conducted to examine the relationship between heuristics biases and stock buying decisions of individual investors at the Nigerian stock exchange. Table 4.5 summarizes the analysis results. As can be seen each of the heuristics variables is positively and significantly correlated with the criterion (stock buying decisions), indicating that those heuristics variables with higher values tend to have higher influence on the investment decisions.

The multiple regression model with all the five predictors (heuristics variables) produced $R^2 = .563$, $F(5, 211) = 79.31$, $p < .001$. As can be seen in Table 4.4, availability bias and Gamblers fallacy had the highest regression weights, indicating that investors exhibiting the higher level of these heuristics, their investment decisions would be highly influenced by such biases, controlling for the other variables in the model. Representativeness and Anchoring did not significantly contribute to the multiple regression model, indicating they have little influence on the stock buying decisions.

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Table 5: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics		
					R Square Change	F Change	S
1	.808[a]	.653	.644	.556	.653	79.308	.

a. Predictors: (Constant), Overconfidence, Representativeness, Gamblers' Fallacy, Availability Bias, Anchoring.

b. Dependent Variable: InvestDecMaking

The ANOVA table is utilized to test whether the model we proposed (the regression line) is significantly better at foreseeing stock purchasing choices from heuristics factors than if we just utilized the mean of the stock purchasing choices. "F" is the estimation of the ANOVA test statistics which is utilized to evaluate regardless of whether the watched estimation of F is large to the point that it is probably not going to have happened by chance. It demonstrates the likelihood of getting an estimation of F as substantial as our acquired one, simply by chance. Since our Significance level is .05, we can infer that our estimation of F proportion (79.31) is large to the point that it is probably not going to have happened by chance; our regression line is a fundamentally preferred fit to the data over a model based on utilizing the mean of the values for the stock purchasing choices.

Table 6: The ANOVA Table

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	122.779	5	24.556	79.308	.000[a]
	Residual	65.331	211	.310		
	Total	188.110	216			

a. Predictors: (Constant), Overconfidence, Representativeness, Gamblers fallacy, Availability Bias, Anchoring

b. Dependent Variable: Stock buying Decision

4.3 Implications of the findings

The findings of this study have implication for individual investors. The individual investors can benefit directly from the findings of this study as it makes them aware that these biases prevail among them while making their investment decisions, which may have implications on their investment performance. The findings of this study call for proactive measures to be taken by the security market operators on the need for enlightenment on general financial literacy to enhance rational decision making in the stock market to debiased such biases. The security operators can use these findings as reference for their analysis, and for predicting the trends in the security market. The implications of these heuristics are multidimensional on individual investors. First, investors who exhibited anchoring heuristics will be more likely to buy stock that can give return different from their expectations. For example, if investors based their decisions on historical high stock prices and expect the stock to recover, they may continue holding their losing stocks for too long (Odean, 1998). Also, they may base their decisions on historical percentage increase in prices and expect a similar trend in the future, this can lead them to buying the overvalued stock. Investors exhibiting anchoring heuristics may base their decisions on historical performance of companies which may deviate from their trends of past performance due to some uncontrollable economic factors. Second, the investors who are exhibiting representativeness bias are more likely to buy a wrong stock for their portfolio. For example, they may base their buying decision on insufficient past data, this may lead them to buy a stock that may not have the potential to meet their expectation in future (sample size neglect). Third, investors will choose investments opportunities based on information that is readily available to them (advertising, suggestions from advisors, family, friends, etc.) and will not engage in disciplined research and due diligence to verify that the investment they selected is a good one. Heuristics biases can influence other areas of financial decisions making such as investing, financing, asset management, and dividend policy decisions (Khan, et al, 2017).

5.0 Conclusions and Recommendations

The findings revealed that heuristics biases have a significant influence on stock buying decisions of individual investors at the Nigerian stock market. Individual investors in the market should allow investment professionals like the stockbrokers to manage their portfolios; this will reduce personal biases in managing the investment.

There is the need for the Nigerian Stock Exchange to make information about the fundamentals of the traded stocks much more readily available. This will enable investors to carry out analysis and take an informed decision about the right stock to invest in. Although the findings of this study are encouraging and useful, it has some limitations as most field surveys suffer from. First, the data collected for this study was cross-sectional, longitudinal (secondary) data will be needed in the future to investigate which component of heuristics will continue to influence investors stock buying decisions over time.

The findings presented here were obtained from a single study that focused only on heuristics biases that influence a stock buying decision, while there are other major factors (like macroeconomic variables and investors risk profile) that also influence the stock buying decisions. Thus, another research that combines both heuristics biases, risk profile and macroeconomic variables is needed to have a comprehensive view of all the factors influencing stock buying decisions. As respondents were chosen from ten leading stock brokerage firms, generalization for the whole population is not perfectly fulfilled although random sampling is applied.

This paper is one of the few studies that investigated the influence of heuristics on stock buying decisions of individual investors in Nigeria with the measurements of 5-point Likert scale. It is necessary to have further researches to confirm the findings of this research with the larger sample size and more diversity of respondents.

There is the need to conduct further researches to improve the measurements by incorporating both heuristics variables, risk profile, and macroeconomic variables to have a comprehensive view of the impact of each dimension concurrently. Also, further researches can be carried out to apply heuristics biases to explore their influence on the decisions of institutional investors at the Nigerian stock market.

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